Visualizing Personal Networks: Working with Participant-Aided Sociograms[1]

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Abstract

We describe an interview-based data collection procedure for social network analysis designed to (a) aid gathering information about the people known by a respondent and reduce problems with (b) data integrity, and (c) respondent burden. This procedure, a participant-aided network diagram (sociogram), is an extension of traditional name generators. While such a diagram can be produced through computer assisted programs for interviewing (CAPIs) and low-technology (i.e., paper), we demonstrate both practical and methodological reasons for keeping high technology in the lab and low technology in the field. We provide some general heuristics that can reduce the time needed to complete a name generator. We present findings from our Connected Lives field study to illustrate this procedure and compare to an alternative method for gathering network data.

Past Research

Visual depictions of relations among individuals have been an attraction of social network analysis for many years. Even when network researchers use matrix-based techniques for analyzing clusters, blocks, etc. (Faust & Wasserman, 1992), they often visualize network structures through diagrams. Such diagrams, showing the connections of individuals (organizations, etc.) in specific and relevant ways, provide complex pictures of actors dependent on each other that go beyond the usual sociological representations of independent actors as sets of attributes (Wellman, 1988; Abbott, 2001). Yet for most analyses, these diagrams only appear in the lab long after data collection is complete.

The lack of visual depiction of networks at the data gathering stage obscures data collection because neither researchers nor respondents can see concrete representations of what they are discussing. To be sure, it makes sense to avoid constructing a sociogram when mapping networks of connections among the members of an entire population (‘whole networks’). For studies of whole networks, individuals are only asked to report on their ties to others, but not on

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the ties between these other individuals. Therefore, the sociogram only emerges when the individual lists are combined. However, when dealing with personal networks (or the set of individuals connected to a sampled respondent), the respondent is often the only informant on this network, and any individual in the world could potentially be a member (see McCarty & Govindaramanujam, 2005, p. 62). Yet, the network-as-picture never appears in the interviews. Instead, respondents are subject to a matrix of questions mirroring the matrix used to draw the subsequent network. Since all information about the network is given in one sitting, it should be possible during the interview to collect and structure that information as a social network rather than merely as a social matrix.

In this paper, we describe an extension of the name generator method for such real-time visualization during data collection. Using a name generator, interviewers ask respondents (referred to as 'egos') to name other people (referred to as 'alters') with whom ego has a specific connection. After enumerating a set of alters, ego describes the attributes of these alters and reports on both ego-alter connections and connections between alters (in ego's eyes).

Extensive work collecting name generators began in the late 1960s. Early work includes Edward Laumann's Detroit area study (1973), Barry Wellman's first East York (Toronto) study (Wellman, 1979), and Claude Fischer's Detroit and northern California studies (1977; 1982).[2] These studies show how personal networks were multiplex, varied, geographically dispersed and sparsely knit. For example, individuals would have stronger ties to people with whom they shared more than one social context (such as work *and* neighbor), and urbanites did not have larger or more diverse networks than their peers in the country.

The results from these studies were persuasive enough in their depiction of community ties and social support (see Wellman, 1993) that others sought to include name generators in mainstream social research. In 1984, a short name generator was used in the American General Social Survey (GSS), and led to compelling findings that the core discussion groups of Americans were often small (with a mean of three members), densely-knit, and filled with as many friends as kin (Marsden, 1987; Burt, 1984). In 2004, the G.S.S. replicated these questions and discovered that the number of people Americans discuss important matters with had shrunk by nearly one-third in twenty years to a mean size of 2.1 (McPherson, Smith-Lovin, & Brashears, 2006).

Name Generation Walkthrough

Name generators follow a characteristic structure, one that we employ in our current research. To begin a name generator, respondents are asked to elicit individuals in one of two ways:

1. Free recall with defined scope conditions (e.g., "name all the people you had dinner with in the last week," "name those you are close with" or "name those with whom do you discuss important matters"). The scope condition applies to everyone in the network (the 'Wellman approach').

[2] Networks and milieu affected the production of these studies. Laumann, Fischer and Wellman were each graduate students at Harvard University's Department of Social Relations in the mid-late 1960s, where they were influenced by the work of Charles Tilly and Harrison White (Freeman, 2004).

2. Through a set of questions defining a range of potential or actually supportive alters (e.g., "name someone who could lend you 500 dollars" or "name someone who could babysit your children"). Different questions elicit different alters (the 'Fischer approach').

In both approaches, the interviewer compiles a list of individuals based on these techniques and uses this list for more specific questions. Wellman (1979) and the U.S. General Social Survey (Burt, 1984) use the first method while Fischer (1982), and the Social Survey of the Networks of the Dutch (Flap, et al., 1999) use the second.

Once the alters have been elicited, there are three question types:

Per-network questions: The same question is repeated for each alter before going on to the next question. A variant on this is to ask the respondent to indicate which alters do a particular task (e.g., "Of everyone you named, who gives you financial advice") rather than repeating the question alter-by-alter.

Per-alter questions: For a set of challenging questions (such as communication frequency by media), it is easier to focus on the overall relationship to a single alter before moving to the next alter. (E.g., "How often do you communicate with [alter *x*] in-person, by phone, or by email?") These are sometimes referred to as "name-interpreting questions" (Flap, et al., 1999).

Per-dyad questions: A dyad refers to two network members and the possible relation between them. In order to calculate structural metrics, such as the number of groups and the extent to which the network is clustered, researchers need to know if there is a connection between any two alters or not. The standard method is to about all $\frac{1}{2}(n(n-1))$ possible alter pairs between the n individuals. (E.g., "are A and B close," "are A and C close," and "are B and C close".) The per-dyad questions are used to build the matrix that visualizes the network. In the most simple instance, each row and each column corresponds to an alter. If there is a tie between A and C then the first row, third column contains a 1. Otherwise that cell contains a 0.[3] In many personal network studies, ties are assumed to be symmetric, so if A befriends B then B befriends A.

Until now, visualization has been more common in the lab than in the field. Yet, visualization is a useful means for accelerating aspects of these procedures (such as per-network questions and the per-dyad questions), and it is a useful means for providing reliability checks on certain network measures such as interpersonal closeness.

Although we developed our visualization approach independently, we subsequently discovered that others had also used visualization while collecting personal network data. Maureen Fitzgerald (1978) pioneered visualization in West Cameroon, Africa. Like ourselves, her data collection arranged alters visually, based on interpersonal closeness. Her respondents wrote the names of alters on plastic chips that were arranged in rows on a table so that those alters to whom the respondents felt closest were placed closest to them. Respondents then ranked alters within these rows, from closest to least close. In the United States in the 1980s, Kahn and Antonucci used three concentric circles to arrange network members in their studies of elderly

[3] Most personal network studies discuss symmetric relationships because of the difficulty in reporting on directed relationships between alter-alter pairs. In symmetric networks, the upper right half of the matrix will be a transposition of the lower left.

persons in the United States. As in our approach, the outer circles represented decreasing levels of closeness, and respondents found this level of nesting to be intuitive and intelligible (Antonucci, 1986). More recently, Ray Pahl and Liz Spencer (2004; Spencer & Pahl, 2006) have used concentric circles of closeness to map ‘personal communities’ – a conceptual analogue to the personal network.

There has also been recent work employing computer-assisted visualization as a data capturing and interviewing technique, apart from the use of concentric circles. Chris McCarty and Sama Govindaramanujam (2005) have recently used network visualizations in their EgoWeb program to gather information about alters and assist ego in recalling alters.

Unlike the former studies, we include data on the relationships between alters, and unlike the latter study by McCarty and Govindaramanujam we draw the network using the concentric circle concept. Moreover, we treat the concentric circles as a modification of the name generator technique rather than as a separate data generation tool.

The needs to arrange individuals *and* to draw lines between them create a series of practical challenges that are addressed by this paper. We believe that our paper-and-pencil approach stands alongside the trends towards computer assisted techniques. We provide design guidelines and address challenges, and we present the practical and conceptual reasons why we believe the use of computers should be kept in the lab, and low-tech used in the field.

Criticisms of name generators:

As a longstanding social network technique, name generators have had their share of criticism. Such concerns fall into four broad categories: reliability, generalizability, specificity, and cost.

Reliability: By trusting individuals to remember network members and alter-alter ties, we are left to the mercy of a respondent’s cognitive biases. In a follow-up to the first East York study (Wellman, 1979), Norman Shulman discovered (1972) that only a minority of strongly-tied alters named egos back as one of their strong ties, although they most likely were thought of as somewhat weaker ties. Further doubts about respondent recall stem from the research of Bernard, Killworth and Sailer (1979) that showed little overlap between the communication networks of individuals and their self-reported networks. Hence, they claimed that self-reported data on ties should not be taken as reliable indicators of actual behavioral data. Reanalysis of this work has demonstrated that the errors made by respondents were not random but biased against infrequent and fleeting contacts (Romney & Faust, 1982). In fact, individuals appear to be good at recalling networks of individuals with whom they have repeated interactions (Freeman, Romney, & Freeman, 1987).

Accepting that recalled networks are cognitive networks should not inhibit work in this field (see the arguments by Krackhardt, 1987; Batchelder, 2002). Instead, it requires us to make a clear theoretical link between the questions we ask and the means of data collection. For example, in our Connected Lives study, we are looking at alters with whom people frequently communicate and to whom they turn for social support. These questions are grounded in the immediate perceived network around ego, and they mesh with personal network techniques.

Generalizability: Most personal network studies gather their data by surveying a random sample of a population, such as the adult residents of Detroit. Because the samples reflect a small percentage of the population, metrics about overall network structure are difficult, if not impossible, to calculate. For example, eigenvector centrality, or being connected to highly connected individuals, is wildly unstable with the absence of even a few important individuals (Costenbader & Valente, 2003). Nevertheless, much comparative structural work can still be done. For example, Laumann (1973) uses personal network data to report on inter-ethnic ties in Detroit, while Ferrand, Mounier and Degenne (1999) similarly describe the French class structure by examining who in what jobs had ties with people with other jobs. In most cases, such analyses involve metrics that compare personal networks, rather than discuss overall connectivity in the population.

Specificity: Name generators usually are restricted to the strongest *n* ties, where *n* could be as small as 5 people (as in the U.S. General Social Survey: see Burt, 1984; Marsden, 1987) or as large as the maximum of 66 in the Connected Lives study we describe later in this paper. Yet even 66 is hardly the entire network, which usually contains several hundreds or even thousands of friends, relatives, workmates, neighbors and acquaintances (McCarty, Killworth, Bernard, Johnsen, & Shelley, 2000; Pool & Kochen, 1978). For example, Jeremy Boissevain's (1974) pioneering and painstaking study of a Maltese personal network found that the ego had a network of 1,750 persons "whom he had met or had dealings with in the recent or distant past: they formed the social universe of persons who could help him solve his problems" (p. 36). The friends of this ego's friends undoubtedly encompassed a large fraction of Malta's population at the time.

Boissevain's work suggests that the comparatively small set of strong ties captured by personal network measures may not even be the most relevant ties: weaker ties may be more useful for finding jobs in affluent and less developed societies (see also Granovetter, 1973; 1983; Espinoza, 1999) or acquiring cultural capital (Erickson, 1996). Hence instruments to assess other aspects of the network have emerged. Both the *position generator* (Lin, Fu, & Hsung, 2001) and the *resource generator* (Van Der Gaag & Snijders, 2005) are efficient means of capturing a large spread of ties for specific purposes. In our Connected Lives study, high social activity and social support were criteria for including alters in the network. Thus, we specified the network by restricting inclusion to egos' active or supportive ties, and excluding the hundreds of other ties that did not meet these criteria.

Cost: Surveys using name generators are an expensive way to document personal networks. They require between 5 minutes for a quick listing of core ties (Burt, 1984) to several hours for detailed discussions of scores of ties (Wellman & Wortley, 1990). They involve a great deal of repetition because the same questions are asked about each network member. The repetition is even greater when questions are also asked about ties between alters. The researcher has to decide if the time taken and the respondent burden is worth the specific data collected.

Implementation

The goal of the Connected Lives study is to assess the role of communication media in everyday life and its impact on personal networks. To this end, our survey and interview schedule contain a mix of questions about technology use and personal social relations. Data collection occurred in two stages. First, we gave a drop-off survey to a random sample of 350 English-literate adults (18+) in East York, a former borough of Toronto just east of the downtown core with a population of 114,000 (2001 Census) that our research group had studied twice before (Wellman, 1979; Wellman & Wortley, 1990). Additional details about respondent composition and East York's population are available in Wellman and Hogan, et al. (2006).

We followed up the survey with detailed interviews with a 25 percent subsample (87 cases).[4] We included a name generator in the interview portion of the study to obtain details on the respondent's social relations and a per-alter assessment of communication habits. An extensive treatment of the theoretical motivations for this particular name generator is in Carrasco, Hogan, Wellman and Miller (2007). It discusses the potential for integrating models of social activity travel and communication behavior, conditioned on social network metrics and geographic distances between egos and alters.

Doctoral students centrally involved in the Connected Lives study did all of the interviewing. The interviews lasted two to four hours (usually in the evening) and contained the name generator described below. All interviews took place in the interviewee's home. Since the largest prop was 22 inches by 17 inches, most interviews took place at a kitchen or dining room table. The full process of generating names, sociogram layout and in-depth discussions about the alters took between 40 minutes and 90 minutes. The time depended mainly on respondent motivation and network size.

Name Generation

In the interviews, we begin the name generator by highlighting the distinction between 'somewhat close' alters and 'very close' alters (Boase, et al., 2006; adapted from Wellman, 1982):

> ***Very Close:*** People with whom you discuss important matters with, regularly keep in touch with or are there for you when you need help.
>
> ***Somewhat Close:*** People who are more than casual acquaintances but not very close.

Once the distinction is clear to the respondent, the interviewer presents a five-layer name template (Figure 1). The top layer on both sides is a piece of heavy cardboard with three windows cut out. Inside these windows are 33 Post-it® Ultra Page Markers (sized 0.5 x 1.75 inches, hereafter referred to as name tags). We selected these name tags for two reasons. Firstly, they are large enough for most people to clearly write a single name and some other details. Second, the Ultra Page Markers come in a variety of colors. We use a different color for very close and somewhat close alters (and we use pens of the same colors to draw lines between very close and somewhat close ties). The layers are held together with binder clips so that once respondents have finished eliciting names, the top layers can be removed making it easy to relocate the name tags to a large sheet of paper.

> Figure 1 about here <

Each name tag has a small index number in the lower right corner (from 1-33 on each side, see Figure 1 detail). This number records the rank order in which the respondent recalls the alters. When placed correctly, the respondent is neither distracted by the rank number nor

[4] As one respondent was unable to complete the name generator or use any of the other props we had in the survey, the counts for network measures are N=86.

inadvertently writes over it. This rank number can also be used for later analysis. For example, we use the rank number later in the interview as a means for sampling the network.[5]

Respondents are given the name template and asked to fill out people's names in order of free recall, beginning with those with whom they are very close. After respondents feel satisfied that they have included all very close alters, they flip over the template and write down the names of somewhat close alters. Respondents often flip between the somewhat close and very close sides. After they stop entering names, we show them a card listing 8 role categories: 1. Immediate family outside the house, 2. Other relatives, 3. Neighbors, 4. People you currently work/ go to school with, 5. People you only know online, 6. People from organizations (bowling, club, church, team), 7. Friends not included above, 8. Other. We then ask respondents to scan the card and see if they have forgotten anyone from a particular role.

When this task is completed (usually quickly), we ask respondents to write a number next to each alter's name that denotes the alter's role, such as immediate family, etc. Respondents are told it is permissible to write more than one number if a person fulfills more than one role. This process leads to a series of name tags completed much like the one detailed at the bottom of Figure 1. At no point are respondents prevented from adding additional names.

Respondents have considered this process to be user friendly, and it is also a quick way of generating names. The overall distribution of the number of ties is shown in Table 1. Only 3 of the 86 people hit the ceiling of 66 alters (see "total" column in Table 1). In general, people who list a large number of very close alters also list a large number of somewhat close alters ($r=0.70$, $p <0.001$).[6]

> Table 1 about here <

We elicit all names before proceeding to the next task. We do not hint to the respondents that mentioning extra names will mean extra work (even though it does). We neither encourage respondents to achieve a baseline of *n* alters nor to match the total number of alters they reported on the survey. This approach provides unbiased numbers of very close and somewhat close alters, since respondents appear to be emotionally invested in making sure that they include all the people they believe are important in their lives. Indeed, when individuals forget an important person, they often are embarrassed and apologetic.

Organizing the network

The reason for the elaborate name template as opposed to a simpler list on a sheet of paper is so that the names of alters can be relocated to a large sheet of paper. The sheet contains four concentric circles. The name tags are 1.75 inches in length, and the circles increase in radius by two inches so that tags on one ring do not overlap with tags on the next ring. To facilitate this process we use two 11 x 17 inch sheets taped together, making the actual sheet a very sizable 22 x 17 inches.

While the large sheet is somewhat unwieldy, it has a number of distinct advantages:

[5] See also Alexandra Marin's (2004) work detailing the relationships between network density and recall order.

[6] All correlations in this paper employ Pearson's product moment correlation.

1. It gives the participants a large amount of space in which to layout the tags. This larger space also makes it easier in the coding phase to distinguish ties drawn in the interview.
2. Unlike small laptop computers, these sheets enable participants to see all of the alters at once. Many participants find this a satisfying and heady experience. The sheets simultaneously enable the respondents to consider alters in relation to the overall structure.
3. Unlike computer-aided programs, there is little chance of power failure, intimidation with technology, crashes or other complications.
4. Most participants find the task to be creative and fun. By contrast, early experimentation with using a laptop computer to record the network found that it intimidated respondents and was slower than our subsequent paper-based procedure.

Pre-testing led us to a specific algorithm for laying out the alters and drawing the ties between alters. When laying out the tags, respondents were given four instructions:

a) Place tags on the lines, not between them.
b) The circles represent closeness, so place the closest people to you on the inner circle, and work outwards.
c) Place people who know each other close together.
d) Rearrange ties until you are satisfied.

These instructions lead to a unique but often quite orderly social network much like the one featured in Figure 2a, which is a rendering of an actual sociogram collected in the field. We start with the very close tags (denoted by one color), and continue with the somewhat close tags, denoted by another color. One of the advantages of having four rings denoting four possible ranks of closeness is that it allows participants to reassess the binary division of ‘very close’ and ‘somewhat close’ mentioned above.

> Figure 2 about here <

Results: By arranging alters visually we learned that many respondents have some very close alters who are extremely close and others who also are very close but are not extremely close. The mean of 6.5 extremely close (innermost ring) ties we found in the Connected Lives study are more than three times as large as the mean of 2.1 ties in the 2004 GSS’s core discussion network module (McPherson, Smith-Lovin & Brashears, 2006). While these ties are not directly comparable to the GSS’s core discussion network, they highlight how network size – even among the most intimate ties – can vary by method.[7] Moreover, it seems that ‘discussing important matters’ (the criterion used on the GSS) does not capture by itself the full breadth of the most intimate ties.

> Table 2 about here <

As expected, many very close ties are also present on the second ring. More curious is that 9 percent of ties initially labeled ‘very close’ appear on the outer third and fourth rings. However, the 0.5 percent of very close alters placed on the outer ring come only from four

[7] This fact was unfortunately lost in the media panic about “social isolation in America” (Piccalo, 2006).

respondents, two of whom have three very close alters on the fourth ring and two who have one. These alters are consistently among the lowest ranked very close alters (such as the 17th, 20th and 21st of 21 very close alters), and they are not connected to the largest component.

Ties labeled 'somewhat close' are well distributed across rings two through four, with most on the third ring. There is some cognitive overlap between the weakest very close ties and the strongest somewhat close ties, a feature that is captured in the four ring schema. Like the small number of very close alters on the outer ring, the 5 percent of somewhat close alters on the inner ring were rarely connected to the largest component. But unlike the marginal very close alters, these few somewhat close alters who are on the inner ring were recalled early in the name generation process. As such, we believe they are actually very close alters who were inadvertently omitted during the very close naming stage *because* they are not connected to other very close alters.

Disparities between alters who are initially labeled as 'very close'/'somewhat close' and later placed into more finely grained division by rings reveal an interesting difference in perceptions of socioemotional closeness. In the first task of labeling alters as 'very close' or 'somewhat close', the respondents only considered their individual relationship to each alter. However, when the respondents have to arrange these names on one sheet, they must assess the closeness of alters in relation to each other. At these times, respondents promote some ties to the inner rings and demote others to the outer rings. Capturing respondents' behavior shows a benefit of participant-aided visualization: *Arranging the ties in an overall structure induces the respondent to think about individuals in relation to each other*. Even the pile sort technique (Boster, 1994) does not accomplish this task in the same manner because it hides ties underneath each other.

Eliciting ties between alters

Eliciting tie-level (alter-alter) data is a persuasive reason for using a participant-aided sociogram. Historically, researchers would ask respondents about every alter pair in a personal network in order to develop a matrix of connections between alters. This procedure gets lengthy and tiresome in networks with many alters because a linear increase in alters means a geometric increase in the number of possible ties between those alters. In a network with three alters, A, B and C, we need to ask about A and B, A and C, and B and C. But in a network with 66 alters, this adds up to 2,145 questions. At 2 seconds per question, this would be 71 straight minutes of essentially the same question. Much respondent rebellion would occur, either during this section or the half of the interview that necessarily followed this task.

Our visual procedure addresses this issue in two ways: (a) by asking respondents to report on cliques, and (b) by letting respondents decide whether a tie is present instead of asking them about all possible ties. First, we ask about the presence of cliques of 'very close' ties: "groups where everyone is very close to each other". Since alters are already grouped visually on the pages, most respondents have little trouble identifying cliques. Once identified, the respondent draws a circle around the alters rather than completing all possible pairs.

Second, we ask about 'very close' ties between dyads. For these, respondents simply draw a line between the two alters. We encourage respondents to start in the center of the page (the very closest ties) and look for an alter who is tied to other alters. Then, the respondents move on to the next alters and repeat the procedure.

Third, once respondents finish identifying the 'very close' cliques and ties, we repeat the procedure for 'somewhat close' cliques and ties. We asked about very close ties first because very close cliques and ties can be nested in larger somewhat close groups, such as a husband and wife nested in a group of friends. Although somewhat close ties can also be nested in very close cliques, but both in theory and practice we find this to be relatively rare.

By identifying cliques, we are able to shorten markedly the process of enumerating ties. Additionally, the systematic sweep through the alters to look for pairs reduces the monotony of the task while preserving the validity of asking about every alter pair. Drawing lines rarely takes more than 15 minutes, and respondents often find it to be fun. This is a key advantage of real-time visualization: *By systematically arranging the ties, it is easy for individuals to indicate which alters are connected to each other, and to indicate cohesive subgroups efficiently.*

Results: There is much variation in many network measures. We focus on the number of components[8] and the density of the overall graph. For both measures, ego and ties between ego and alters are excluded. The mean density of the 86 networks is 0.17, which increases to 0.30 when isolates are excluded (Table 3).

> Table 3 about here <

There is a clear negative correlation between density and the number of ties($r=-0.38$, $p<0.001$). This is because density is simply the number of ties divided by the number of possible ties. As noted above, the number of alters increases linearly, the number of possible ties increases geometrically. So it becomes increasingly less likely that the number of ties will stay proportionate to the number of alters. There is also a strong positive relationship between the number of alters and the number of components in a network ($r=0.71$, $p<0.001$). The relationship between network size and the number of components persists when isolates are removed ($r=0.72$, $p<0.001$). This means that larger networks do not necessarily have more isolates that skew the number of components. Instead, larger networks have a greater number of separate groups. The implications of these findings – that larger networks are sparser and less connected will be explored in future work.

Name interpreting questions

Just like asking about thousands of alter-alter pairs, asking many in-depth questions about each alter is an extreme burden on respondents. To complicate matters, three of our research issues require three different sampling criteria. These requirements led us to draw to three partially overlapping samples from the network. To reduce respondent burden, we tried to maximize overlap between all three samples, while focusing on the three research issues:

1. Understanding why an individual is – or is not – considered 'very close'.
2. Developing an extensive social activity and media use profile of one alter per household, oversampling very close alters.

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[8] A component is a sub-graph that has no connections to the rest of the network. Strictly speaking there is only one component in a personal network, since ego is connected to everyone. By removing ego, we can get a better sense of the personal networks that affects ego, rather than ego's effect on the network (see discussion in McCarty & Wutich, 2005). An isolate is an individual who is unconnected to the rest of the graph. It is also the smallest possible component.

3. Elaborating the last time ego and alter socialized in Toronto (leveraging the previous sample).

To deal with these competing demands, we have devised a series of sampling strategies that incorporate the visual arrangement of the sociogram and the recall rank of alters. We do not report here on the results of using these three samples (see Carrasco, 2006), but only on the particular procedures used to illustrate various ways in which the sociograms can support different research issues.

Issue 1 – Reasons for closeness: This first sample includes four alters and asks for specific reasons why each alter is considered 'somewhat close' or 'very close'. To sample the network for four alters, we select the lowest ranked alter from each of the four concentric rings, that is, the alter that was mentioned the earliest for each ring.[9] If the respondent uses less than four rings to name alters, we select an additional individual from the inner rings, starting with the closest ring and moving outward until we have four alters.

Issue 2 – Social activity and communication profile: For as many alters as possible we want to know detailed information on their age, employment status, geographic location, socializing habits and media use, including email, instant messaging, traditional landline telephone, and mobile telephone. Constructing these network profiles requires a compromise between the extent of detail and of completeness. Since we ask up to 23 discrete questions per alter, the repetition inherent in the task can be taxing on both interviewer and respondent. Moreover, the interviewer has limited time and has to complete almost 40 minutes of material after the network section. Hence, we do not ask for a profile of all possible alters. Since previous research (Manfreda, et al., 2004) has shown that online respondents are likely to abandon the name interpreting task after 15 alters, we interpret this number as a reasonable baseline for respondent burden. Moreover, our interviewers report that discussing 15 alters is near the respondents' limits of tolerance. We also believe that 15 alters are sufficient to capture the spread of most networks.[10]

Again we employ the rings and the rank order. We use the following algorithm:

1. Only include one alter per alter's household.
2. Include the three very closest (lowest ranked) alters from the inner ring.
3. Then starting on the inner ring, select the lowest ranking person (from either a somewhat and very close tag).
4. Proceed to the next ring and select the lowest rank. (If you are on the outermost ring, return to the innermost ring.)
5. Stop when you have selected 15 people or have run out of alters.

[9] Since rank is a measure of recall order, the lowest ranking individual is number 1, and the highest rank possible is 33 (for both somewhat close and very close alters).

[10] One network analyst at the American Sociological Association's annual meeting (Montréal, August 2006) opined in a panel that researchers should never put ceilings on the number of alters about whom they collect information. When asked if he had ever had to deal with respondent burden in collecting network data, the panelist shrugged.

Using this strategy, we profiled about half (51%) of all alters. However, the profiled alters are an inherently biased sample because of the purposive sampling described just above. We first oversample the inner ring and then sample alters of a lower rank on all of the other rings. As such, we should expect that sampled alters are disproportionately ‘very close’, with a lower rank and in a lower (inner) ring. However, we should not expect to find significant variation on alter attributes, except where these attributes vary with rank and closeness.

Results: We used logistic regressions to predict the odds of an alter being profiled, and report here on the preferred model where variables with $p >= 0.1$ are excluded (Cox and Snell $R^2 = 0.323$, N = 2044). Being ‘somewhat close’ decreases the odds of being profiled by 0.67 (b=-0.41, $p < 0.001$). A unit increase in order decreases the odds by 0.77 (b= -0.258, $p < 0.001$). An increase in rank order of one standard deviation (7.2 units) decreases the odds by 0.15 (b=-1.85, $p<0.001$). Therefore, we are less likely to profile alters who are recalled relatively late. When controlling for rank and closeness, ‘which ring?’ is not a significant predictor of whether an alter would be profiled. That is to say, the sample worked as expected in gathering low ranking alters from all 4 rings and not relying too heavily on any particular ring.

All demographic variables are non-significant in the preferred model except one: being an extended family member decreases the odds of being profiled by a factor of 0.69 (b=-0.37, $p = 0.02$). Thus, we have not oversampled on gender or any of the other statuses (immediate family, friends, workmates, etc.). We believe the difference for the extended family is an unintended consequence of only selecting one alter per household for profiling. Respondents are more likely to include the spouses of relatives than the spouses of friends or workmates: spouses of kin, as in-laws, are often socially closer members of networks than spouses of non-kin (see also Wellman & Wortley, 1989). In the English language, there are ‘sisters-in-law’, but not ‘friends-in-law’.

In terms of advantages, this procedure gathers a broad spread of alters, with little demographic bias and a concentration among the closer ties. It allows us to gather a substantial amount of detail about a sufficient number of close alters and to keep the monotony of this task to a minimum. It enables us to purposively sample particularly relevant alters and ensure that the sample is consistent across respondents and interviewers. Iterating between the four concentric rings enables the sample to be spread evenly between the closest alters on the inner ring and the more marginal alters on the outer ring. Moreover, this procedure works just as well if the respondent does not use all four rings.

In terms of limitations, by using a ranking based on recall order, we oversample alters who are recalled early. Second, this technique is cumbersome to explain to interviewers and is mysterious to respondents.

Issue 3 – Social activity in Toronto: We are also interested in qualitative narratives about social activity with alters living in Toronto. We are able to leverage the previous sample (for Issue 2) for this study because we already have rich descriptions of some network members from it. Therefore, we ask respondents to select 5 of the 15 people in the previous sample. We ask respondents to discuss the last time they socialized, how they traveled, how long it took, etc. The most important criterion for this research is that ego and alter socialize in Toronto, so if less than 5 of the 15 individuals in the previous sample socialize in Toronto, we select the most social individuals from the remaining set.

Per-Network questions: The sociogram as conversation aid

The final task directly involving the sociogram concerns social support. We ask seven questions relating to different dimensions of social support, such as "People with whom you have discussed important matters."[11] For each of these items, we ask the respondent to scan the sociogram and point out people who gave this type of support. We say these names out loud and subsequently code the results from the recordings of the transcripts.

In sum, the sociogram works well as a research aid for these sorts of network questions, and it could be replicated with a variety of topics such as "which of your friends smoke" or "who do you see at Christmas." We believe this strategy is more straightforward than the alter profile discussed above and in some circumstances can be used instead of an in-depth per-alter profile.

Coding

A drawback of our technique is the difficultly of coding a paper-based sociogram. Most network analysis programs expect the researcher to start with a matrix of alters which the program converts into a visualization. We do the reverse, starting with visualization and produce a matrix for analysis. While some computer programs exist that allow the researcher to draw the network and have it converted into a matrix (such as *Visualyzer*, *NetMiner* and *Agna*), none of these programs capture all of the features of our particular network. First, we draw cliques as ellipses, something no drawing program provides. Second, we provide an efficient means of distinguishing 'very close' ties from 'somewhat close' ties. We have built our own program *(NameGen)* which embeds these features in a customized graphical interface tuned to our needs.[12] While researchers could code this type of network in a spreadsheet program, coders would have to be trained to enter cliques tediously by hand.

Our procedure produced approximately 4% errors on relational data and less than 1% error on alter data: Dual entry – a second round of coding – revealed discrepancies in 1 out of 25 codes of information about relationships and 1 out of 100 codes of information about alters. These errors were primarily omissions rather than erroneous additional data. To code a single social network took approximately 80 minutes: 20 minutes per network, 15 minutes for attribute data and the mini-survey (doubled to 70 minutes, given that it is dual entry), and 10 minutes for checking discrepancies between in the dual entered data.

Comparative Results

All interview respondents had completed a survey several months prior that used an alternative method for estimating network size known as the summation method (McCarty, et al. 2000). This instrument breaks up the cognitive burden of estimating network size into manageable chunks, such as kin, workmates and friends. Boase, Horrigan, Wellman and Rainie

[11] The other questions are: "Advice about new job opportunities," "Care for a serious health condition," "Help with home renovations," "Help looking for information about a health issue," "Advice on using a personal computer," and "To be there just to talk about the day".

[12] *NameGen* was developed by a team led by the first author, is open source, and is available at http://www.chass.utoronto.ca/~wellman/software/NameGen/. The most recent version of the program enables researchers to customize the number of possible alters, per-alter attributes, and per-network attributes.

(2006) further subdivided the network into ‘very close’ and ‘somewhat close’ ties. The Connected Lives survey follows Boase, et al. in using the same definitions of ‘very close’ and ‘somewhat close’ ties and similar definitions of roles such as kin, workmate, etc. Hence, we can compare the same respondents’ reports on their network by the summation method with the name generator described here.[13]

The summation method asks respondents to enumerate alters in 16 distinct categories (the 8 roles mentioned above for both the ‘somewhat close’ and ‘very close’ categories). The name generator described in this paper asks respondents to elicit alters as ‘very close’ or ‘somewhat close’, and *then* identify the roles of the alters. A comparison of these techniques by role is not entirely valid since the name generator method allows alters to have more than one role. Moreover, it is possible – although not probable – that the composition of a respondent’s personal network could have changed significantly in the few months between being surveyed and being interviewed.

Nevertheless, we have more data than others to compare the two methods’ estimates of the number of ‘very close’ and ‘somewhat close’ alters. There is a strong correlation between the network size produced by the summation method and that produced by the name generator method ($r=0.67$, $p<0.001$). That is to say, people who say they have few alters on the survey, mention only a few during the interview; those who say they have many on the survey, mention many during the interview (Figure 3). The strength of association is higher for very close alters than for somewhat close alters (very: $r=0.74$ $p<0.001$, somewhat: $r=0.49$, $p<0.001$). This means that the responses given for very close ties vary less between the survey and the interview than responses for somewhat close ties. Respondents seem to have surer grounds for deciding who their very close ties are than their somewhat close ties.

> Figure 3 about here <

Although the number of ties produced by the name generator and the summation method are strongly correlated, respondents routinely mention a greater number of network members when they use the summation method. To estimate the difference in magnitude, we use bivariate linear regressions with no intercepts. Using this measure, the coefficient for the independent variable indicates how far the dependent variable deviates from the diagonal (1:1 relationship) conditioned on that variable, and the R^2 measure indicates the variability of this deviation. Respondents name 1.25 ‘very close’ alters on the survey for every ‘very close’ alter on the interview and 1.64 ‘somewhat close’ alters on the survey for every ‘somewhat close’ alter on the interview. In total, they name 1.47 alters on the summation method for every one on the name generator ($R^2=0.78$).

It is not surprising that respondents disproportionately name more somewhat close ties on the survey, and have more variation in the number of somewhat close ties named. While very close ties are defined by specific criteria, somewhat close ties are defined in the survey as simply “more than just casual acquaintances, but not very close”. By contrast, interview respondents have to actually *name* their alters instead of giving an approximate count. As a result of this

[13] Analysis in this section includes 81 respondents. It excludes three respondents because of missing data on the summation method, and it also excludes two respondents who gave wildly divergent numbers in the survey-based summation methods and the interview-based name generator (i.e., 6 somewhat close alters on the interview versus 120 on the survey).

procedural difference, respondents are choosier in the interviews about which alters are somewhat close. Moreover, some survey respondents round off large counts on the survey. For example, one person reports being somewhat close to 40 fellow members of a voluntary organization. The true number is probably not as tidy.

We believe that the name generator technique is preferable to a summation method for ascertaining a consistent and accurate measure of the size of an individual's close personal network. By requiring respondents to elicit specific alters, respondents are less likely to round the number upwards and are more careful with their definition of somewhat close ties. However, the name generator is time consuming and burdensome to both interviewers and respondents. Despite the limitations of the summation method, it can still give an effective measure of the variation in network sizes between respondents, and it is much simpler and quicker for interviewers to administer and for respondents to self-administer. Hence, it remains useful for the many studies which have limited time to collect personal network information.

Discussion

Advantages:

Interview quality**:** Experience has shown that respondents enjoy using the name generator as a visual sociogram. This method improves interview experience when compared to name generators that ask about all alter pairs. Respondents routinely comment on how interesting their personal network looks and how they never considered it in such a fashion. Guidelines for ethical reviews often cite "personal insight" as a benefit to the respondent from social science research. We believe that we can stand by this claim for the participant-aided sociogram.

Reliable structures**:** Since respondents view alters in relation to each other, they can provide a more holistic view of their relationships. This is evinced in their frequent reassessment of closeness when they lay out the 'very close' and 'somewhat close' name tags.

Paper makes sense**:** This is a twofold point. First, paper is cheaper and easier to set up than a computer. It is less intimidating to many respondents, particularly those not comfortable with computers. Paper does not crash or have power failures, and there is no file which the interviewer can accidentally forget to save. Moreover, it is easier to alter a paper-based strategy to suit particular needs than a software-based strategy.

Second, paper is intelligible. Since paper strips down the data collection to only the necessary parts, respondents believe that the picture of the network is something they have created in active collaboration with the interviewers, rather than something the computer created for them.

Richer data: By contrast to traditional matrix-based ways of obtaining personal network information, using the visual sociogram is more efficient. Within a given time frame, it increases both the number of alters that respondents describe and the amount of detail that respondents provide about these alters.

Lower cost: The per-respondent cost is only a few dollars for Post-its® and a large sheet of paper. The capital costs are also low: Per-interviewer, the cost is about US$20 for a set of colored sharp-point markers, and heavy stock for making name templates in addition to the hand labor for creating the templates featured in Figure 1.

Disadvantages:

***Interviewer burden**:* When implemented well, the sociogram procedure is intelligible to respondents. However, it involves substantial training of interviewers. This can be contrasted with CAPI (computer assisted programs for interviewing), which automatically handles most of the sampling, sequencing and layout of interviews. However, interviewers have to be trained on how to handle CAPI itself.

Props: The sociogram procedure is very heavy on props. We use a specific name template, a very large sheet, specially chosen Post-its®, colored pens, and stimulus cue cards (such as a list of possible relationships). Interviewers invest significant time ensuring that all of this material is available and ready before each interview.

Paper: Interviewers must take care not to lose the paper sociogram and to keep the Post-its® securely attached to the large paper sheet, which fortunately can be folded in half to help secure the Post-its®. Although we take photos of each sociogram, this is not as useful as having a backup computer file.

Size: 22 x 17 inches is a large sheet of paper whose use requires interviewers to sit with respondents at a large table, usually the dining room table. This may not be the most convenient place for the respondent to talk.

Interviewer variation: There is variation between our six interviewers in the number and structure of ties they elicited. The number of ties varies from a mean of 18 for one interviewer to a mean of 30 for another (see Table 4). However, the standard deviations are quite high (between 9 and 19), suggesting much per-interviewer variation. Hence, we believe that the variation in the size of networks is only partly attributable to variations in interviewer quality. There is less per-interviewer variation in the ratio of 'very close' to 'somewhat close' alters, and in the density of the network (when controlling for network size).

> Insert Table 4 about here <

Things we would change:

Clearer guidelines: Variation between interviewers can be reduced by providing: (a) systematic guidelines for knowing when to stop searching for new names, and (b) providing more clarity in what constitutes a 'somewhat close' alter.

Sixty-six alters is too low a ceiling: While the name template we used could only hold 66 alters, a small number of respondents would benefit from being able to name even more, and the 22 x 17 inch sheets for laying out the networks can certainly hold even more. We propose that interviewers carry a second template in case respondents run out of name tags.

A more straightforward sampling frame: Our heuristics for selecting a sampling frame were difficult to communicate and included some biases – acceptable to us in this study but probably reducible for the future. In retrospect, we would have liked to gather the same amount of information more randomly. To reduce bias, we propose pre-generating a list of random samples based on networks of varying sizes. These sampling instructions would be given to interviewers ahead of time.

Conclusions:

Name generator procedures are a data rich and compelling way to capture an individual's social network. These procedures have been with social network analysis for most of the field's history: at least since J.L. Moreno's pioneering sociograms (1934; see also Freeman, 2004). However, they are complex and time consuming. We have presented a name generator procedure in which respondents visually arrange alters during an interview. Using this sociogram procedure in interviews, respondents place the names (written on small Post-its®) on a large sheet of paper with four concentric circles. This procedure allows interviewers to work closely with respondents to identify the strength of relationships, to efficiently capture ties between alters, and to sample alters purposively. The visual nature of the procedure and the moveability of the Post-its® also enable respondents to reassess certain metrics (such as socioemotional closeness) by considering members of their personal network in relation to each other.

Using a paper-based method for visually arranging ties is preferable in many ways to computer-based alternatives. It is more dependable, pleases respondents, looks visually compelling, and can be seen at once (making it a useful prop in addition to a data gathering technique).

Yet, we are not wholly against computer-based methods. We have had to build our data entry software from scratch in a time-consuming way and using programming expertise that is not generally available to social scientists. We continue to assess the proliferating tools available for social network analysis.

It is not that we necessarily recommend against CAPI tools. Rather, we encourage researchers and software developers to keep in mind some of the advantages we have encountered by using a paper-based visualization technique. During the interview, every effort should be made to draw out information in the most stimulating and straightforward manner possible while seeking to minimize interviewer and respondent burden. With these goals in mind, we believe that a paper-based participant-aided sociogram is a useful approach at this time.

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Table 1: Distribution of alters from the name generator (N=86)

Closeness	Very	Somewhat	Total	
Number of Alters	***Frequency***	***Frequency***	***Number of Alters***	***Frequency***
0	0	2	**0**	0
1-8	37	32	**1-16**	33
9-16	34	33	**17-32**	34
17-24	8	11	**33-48**	14
25-32	4	3	**49-65**	2
33	3	5	**66**	3
Total alters	999	1045		2044
Mean	11.6	12.2		23.8
Median	10	10		21

Table 2: Distribution of alters: ring by label (N=86)

Closeness	Very Close		Somewhat Close		Total	
	Mean %	**S.D.**	**Mean %**	**S.D.**	**Mean %**	**S.D.**
Innermost ring	55.9	22.6	4.7	12.9	30.4	16.0
Ring 2	34.8	18.2	28.0	27.4	32.6	14.6
Ring 3	8.7	13.2	44.9	29.6	26.1	15.5
Outermost ring	0.5	2.3	22.3	28.3	10.9	13.9

Table 3: Distributions of network measures (N=86)

	Isolates	Components	Components (no isolates)	Density	Density (no isolates)
Mean	4.34	8.51	4.22	0.17	0.30
Std. Dev.	4.39	6.20	3.23	0.17	0.28
25th percentile	1	4	2	0.08	0.12
Median	3	7	3	0.12	0.19
75th Percentile	6	10	5.5	0.20	0.39

Table 4: Distribution of network measures by interviewer (N=86)

Interviewer	Number of interviews	Mean (S.D.) network size	Mean (S.D.) density	Mean (S.D.) % "Very close"
1	15	18 (11.5)	0.15 (0.14)	56 (24.1)
2	19	23 (15.2)	0.22 (0.28)	51 (10.8)
3	19	23 (16.8)	0.20 (0.16)	53 (15.5)
4	12	23 (9.3)	0.16 (0.13)	55 (16.0)
5	5	29 (19.7)	0.12 (0.07)	43 (6.1)
6	16	30 (13.1)	0.14 (0.09)	48 (11.1)
Overall	86	24 (14.3)	0.17 (0.17)	51 (15.6)

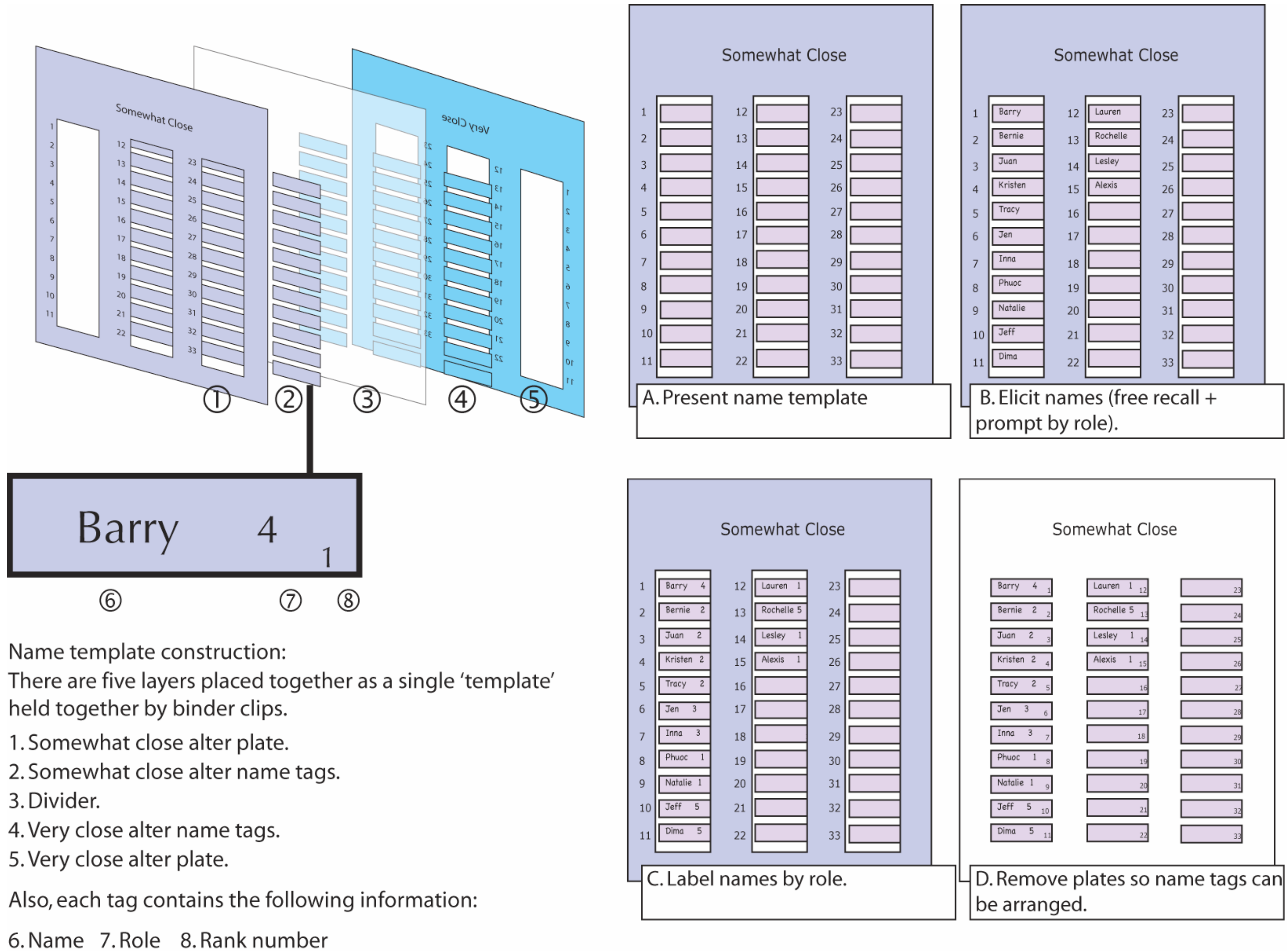

Figure 1. Schema for name template device used to generate names and roles, and partition network by closeness.

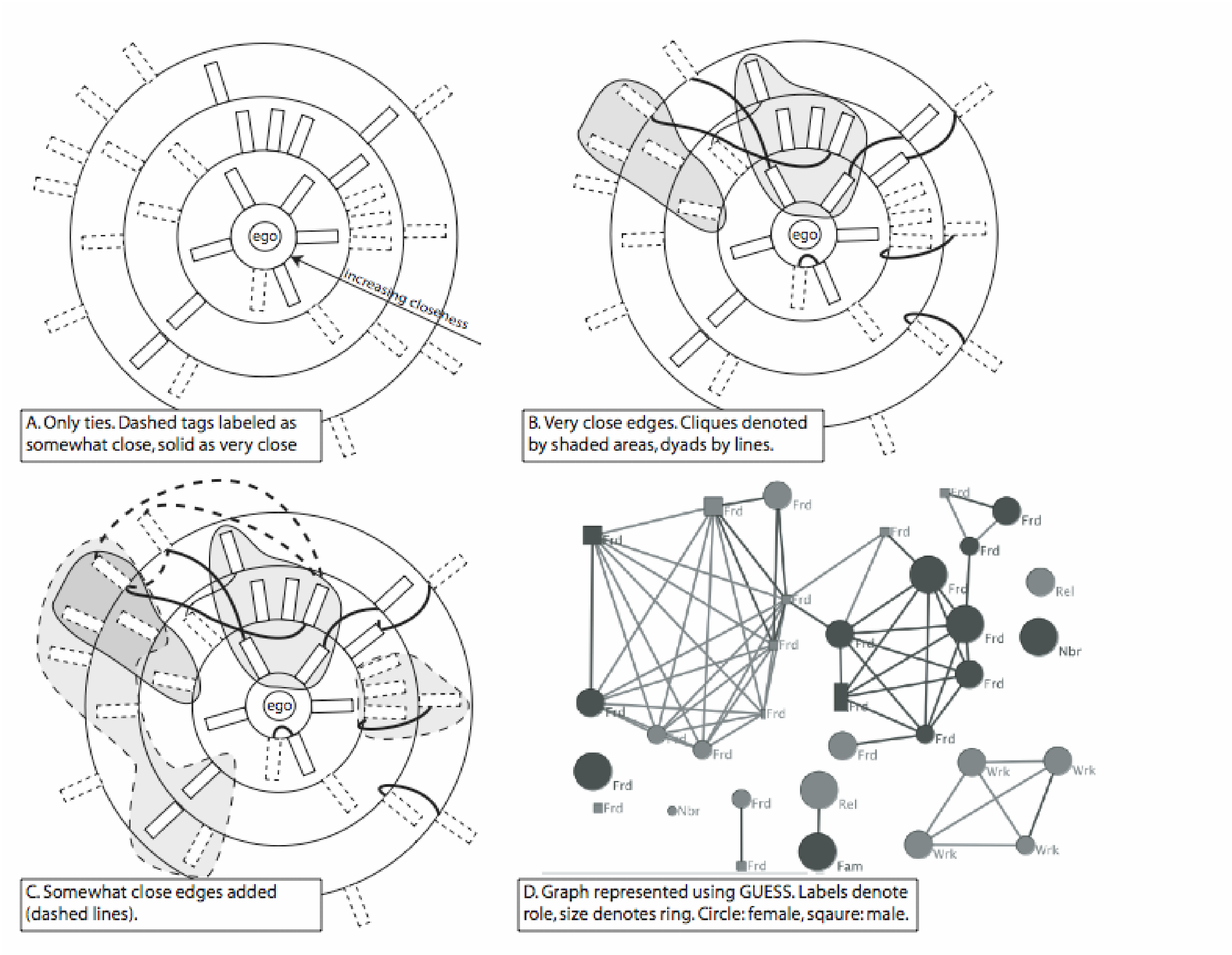

Figure 2. An example social network in four stages of detail. [A] Arrangement of ties [B] Drawing of strong ties, cliques first, followed by edges [C] Drawing of somewhat close ties, cliques first followed by edges [D] Graph as coded and represented using the GUESS Network Visualization software (Adar, 2006).

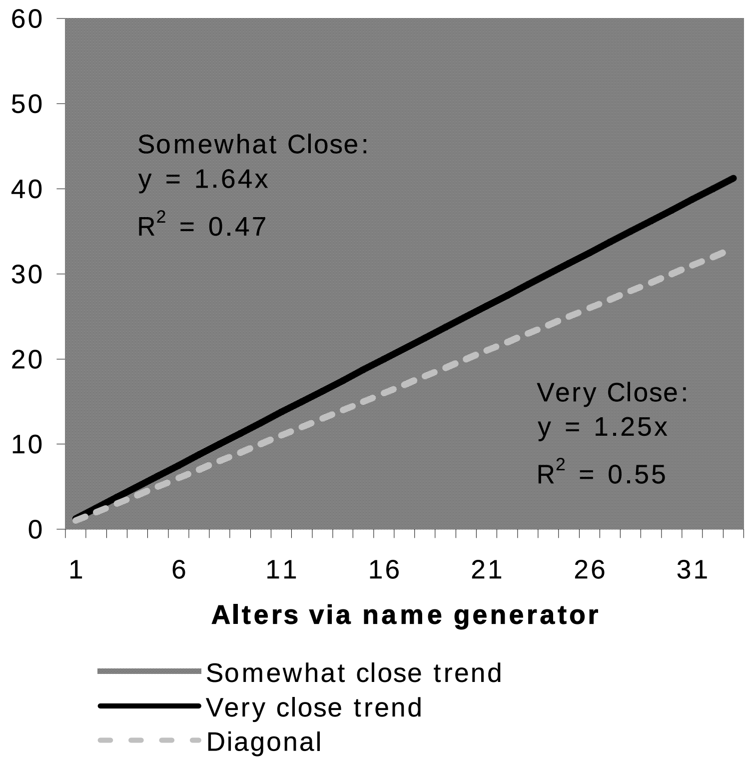

Figure 3. Differences in network size between the interview-based name generator and the survey-based summation method (N=81).